REFERENCES

STEPHEN J. HOCH, BYUNG-DO KIM,
ALAN L. MONTGOMERY, and PETER E. ROSSI*

Using weekly scanner data representing 18 product categories, the authors estimated store-specific price elasticities for a chain of 83 supermarkets. They related these price sensitivities to a comprehensive set of demographic and competitor variables that described the trading areas of each of the stores. Despite the inability of previous research to find much of a relationship between consumer characteristics and price sensitivity, 11 demographic and competitive variables explain on average 67% of the variation in price response. Moreover, the authors found that the consumer demographic variables are much more influential than competitive variables. Their findings open the possibility for more effective everyday and promotional pricing strategies that exploit store-level differences in price sensitivity.

Determinants of Store-Level Price Elasticity

Micromarketing seeks to customize retailing policies to exploit differences across stores in consumer characteristics and the competitive environment. This store-level customization presupposes the existence of significant and identifiable differences in consumer response to retailing policies across stores. To implement a micromarketing strategy, the retailer must develop quantitative measures of relevant aspects of consumer response to different merchandising policies and then adopt a method for computing these measures on a store-by-store basis. The retailer can then implement customized pricing on the store level. In addition, retailers and manufacturers can work together and lever existing promotional expenditures through more precise micromarket targeting of stores. The premise is simple: Spend disproportionately more in stores that are most sensitive to changes in promotion and price.

We focus on consumer response to price changes, as captured by price elasticity measures. Price sensitivity is fundamental to many important aspects of retail policy, including

design of promotions, choice of regular shelf prices, and pricing of private label brands.

Using store-level scanner data from Dominick's Finer Foods (DFF), a major chain in the Chicago metropolitan area, we develop price elasticity measures for each store. We obtain store-level price elasticity estimates in each of 18 product categories. These elasticities exhibit a great deal of variation across the diverse set of DFF store locations, demonstrating that individual stores have distinct price response profiles. These distinct store price profiles for each store provide the necessary condition for successful micromarketing.

To provide insight into the determinants of price sensitivity and for predictive purposes, we then relate our price elasticity estimates to consumer demographic characteristics as well as to measures of the nature and extent of local market area competition. Our findings can be used to predict price sensitivity on the basis of readily available demographic and competitive information for undeveloped store locations, or to help retailers who are unwilling or unable to conduct time- and computer-intensive econometric analyses of store scanner data. A small set of demographic and competitive environmental variables explains two thirds of the variation in the price elasticities across stores. For the most part, there are consistent patterns in the sign and size of the relationship between the explanatory variables and the price elasticities across the 18 categories. We use pooling methods to summarize the information from individual category analyses and provide further evidence on the commonality between categories.

The approach of the paper is as follows. First, we develop a conceptual framework that guides the selection of demographic and competitive variables and review work on the correlates of price sensitivity that uses either household

or store-level data. Sources of data are then discussed. Second, we present the item-level sales response models used to estimate store price elasticities, which are related to variables that measure the store area demographic and competitive environment. The results of the individual category analyses are provided, followed by material on pooling across categories. Finally, we present the implications of our findings for everyday and promotional pricing policies.

CONSUMER AND COMPETITIVE CORRELATES OF PRICE SENSITIVITY

Household-Level Research

We view shopping activity as a part of an overall household production process (Becker 1965). Returns to household shopping, which allow the consumer to take advantage of price reductions, are balanced against various costs, including inventory, transportation, opportunity (time), and search costs. This viewpoint provides some discipline in selecting and constructing variables from the rather large menu of available demographic data.

Inventory or storage costs influence price sensitivity by affecting a household's ability to take advantage of deals. Households with larger storage facilities have the ability to buy larger quantities. Transportation costs also may influence price sensitivity; vehicle ownership increases one's ability to take advantage of deal prices and to stockpile.

Sensitivity to price requires an awareness of the distribution of prices, which requires considerable time and psychological effort. Therefore, factors that influence the opportunity cost of time should in turn drive price sensitivity. From an economic perspective, consumers will make trade-offs between expending time on shopping versus other activities, depending on the returns from each activity.

The prediction is that consumers with high opportunity costs (in particular, wealthy consumers with a high marginal value of time) will be less price sensitive. This implies a negative relationship between price sensitivity and level of education, though some have argued that education might contemporaneously reduce the psychological costs of price comparisons. It also implies that all else being equal, we would expect elderly consumers to be more price sensitive, because of greater leisure time. Moreover, we expect large households to be more price sensitive; because of the large amount of disposable income spent on groceries, the greater the potential returns (savings) from shopping.

Standard economic demand theory suggests that the household allocates disposable income over various expenditure categories, taking into account the relative price indices of each category. Measured household income, however, may play only a small role in determining this price response, because the observed price response of a household to changes in the price of items in any product category depends on many factors.

Blattberg and colleagues (1978) adopted Becker's (1965) point of view in their study of diary data. Using data from the *Chicago Tribune* Panel for five product categories collected over the years between 1958 and 1966, they discovered three demographic characteristics that were mildly predictive of deal proneness: car ownership, home ownership, and households with unemployed wives. However, their data

were collected more than 30 years ago, and the radical changes in the work force and in family structure that have occurred since then may have altered the empirical regularities. Many women work because they have to (e.g., single mother families) and therefore they may be more price sensitive. Income had no effect on deal proneness when controlling for other relevant factors, despite theory suggesting a negative relationship.

Most other attempts to identify demographic correlates of price sensitivity and deal proneness using household panel data conclude that there is a weak to nonexistent relationship (Frank, Massy, and Wind 1972; Montgomery 1971; Webster 1965). In their evaluation of different aggregation approaches to developing market segments, Elrod and Winer (1982) related observed differences in price sensitivity to socioeconomic and demographic characteristics and found only weak associations. Price response increased with age, educational level, and households headed by females. Rossi and Allenby (1993) found little relation between household characteristics and household-level estimates of logit price coefficients. Narasimhan (1984) found relationships between coupon usage and household demographic characteristics. Under a price discrimination theory of couponing, this would suggest indirectly that there is a relationship between price sensitivity and the demographic variables considered by Narasimhan. In related work, Bawa and Shoemaker (1987, 1989) found that propensity to use an off-price coupon increased with education, income (weakly), and household size.

There is also substantial literature that investigates the determinants of price search behavior (e.g., number of store visits and prices paid). The theory is well developed, but there is a paucity of supporting empirical findings. Carlson and Gieseke (1983) found that price search behavior increased with age and was single-peaked with respect to income. Marvel (1976) and Maurizi and Kelley (1978) found an inverse relation between income and search. Goldman and Johansson (1978) related a combination of attitudinal and economic variables to self-reported search behavior. Marmorstein, Grewal, and Fishe (1992) found that the subjective value of price comparison shopping time decreases with wage rates and increases with enjoyment of the shopping process. In all cases, the percentage of variance explained was small ($< 15\%$).

To summarize, previous research at the household level has not been able to explain a very large fraction of variation in price sensitivity on the basis of observed consumer characteristics. There are several possible reasons for lack of explanatory power. First, most of the research has utilized consumer panel data; such data often contains many households with very short or sparse purchase histories. Second, the purchase histories usually involve only one or two product categories and do not capture behavior across the multiple categories that make up consumers' weekly market baskets. Third, in-store and competitive promotional activities may overwhelm any demographic-based consumer price proclivities that might exist, that is, short-term environmental factors swamp individual differences, much as has been found in the field of personality psychology (Mischel 1984). Finally, the variation in demographic attributes is often less

among scanner panel members than in the store populations found in a major metropolitan area.[1]

Store-Level Research

We expect observed price sensitivity to be related not only to consumer characteristics but also to the competitive environment. Price sensitivity can be reflected in switching among brands of the same product category, between product categories in the same store, and across different stores. As the number of alternative retail outlets increases, the household is given more substitution possibilities and should be more price sensitive unless the prices are perfectly correlated across stores.

The competitive environment is determined not only by the number of shopping alternatives or substitution possibilities but also by the cost of search and the format of the competition. The costs of search should increase as a function of the physical distance and driving time between stores. The greater the dispersion of prices in the market, the higher is the expected savings from search. Therefore, we would expect trading areas with greater retail density (more different outlets in a given area) to display greater price dispersion, which in turn drives greater price sensitivity on the part of the consumer.

Most consumers shop at a number of stores, both within and across weeks. Depending on whether a shopping trip is primary (buying groceries to last 1 to 2 weeks or more) or secondary (filling a immediate need resulting from an out-of-stock condition at home), consumers may place more or less emphasis on convenience versus price. Larger stores will tend to attract more primary shoppers (because of wider assortments), whereas smaller stores will attract more secondary shoppers who are interested in convenience.

We might expect that, relative to the competition, larger volume stores would be more price sensitive than smaller stores. To stay in business, larger stores have to draw from larger trading areas; consumers must be willing to drive farther. Consumers who frequent smaller, more proximate stores may self-select on the basis of location and the ability to get in and out of the store quickly rather than on selection/assortment or price.

Store-level scanner data has been used to study this competition between stores. In general, the research suggests that within-store price effects are much greater than those observed between stores. Kumar and Leone (1988) studied the disposable diaper category and found that though there is significant promotion-induced store substitution between proximate stores, within-store substitution rates were two to three times greater. Walters (1991) examined both within-store and between-store substitution and complementarity. Store substitution rates were very low compared to brand switching within a store.

Bolton (1989) used store-level scanner data to relate price elasticities to a variety of variables that characterize the promotion and performance of each brand. She considered the extent of couponing, market share, price activity, and display/feature activity and found that these were correlated with price elasticities. All the variables considered by Bolton are jointly determined by the marketing strategy and not fundamentally explanatory in nature. The characteristics of consumers and the competitive environment studied here are better seen as the primitives that determine price sensitivity.

To summarize, the store-level research has focused on the patterns of substitution between and across stores. In the empirical work discussed subsequently, we examine the relationship between store price elasticity and detailed data on the competitive environment surrounding each store.

SOURCES OF DATA

There were three main sources of data: Dominick's Finer Foods (DFF); Information Resources, Inc. (IRI); and Marketing Metrics. Dominick's has approximately 90 stores and a market share of approximately 20%.

Store-Level Sales Data

Dominick's provided the University of Chicago with weekly store-level scanner data by UPC, including unit sales, retail price, profit margin, and a deal code indicating shelf-tag price reductions (bonus buys) or in-store coupons. The categories are displayed in Table 1. There is an average of 270 UPCs in a product category, from a low of 57 in bath tissue to a high of 637 in cookies. The time span for DFF scanner data is 160 weeks, the first 80 of which are used for elasticity estimation and the next 80 are reserved for model validation. Because some of the stores had limited historical data, we limited our attention to a sample of 83 stores.

Chain and Market-Level Promotional Activity

Information Resources, Inc. provided us with InfoScan data for the Chicago market that was broken out for Dominick's and the remaining competitors as an aggregate; for our purposes, we focus only on Dominick's promotional activity. The IRI data is based on a representative sample of approximately 60 stores drawn from the population of all major Chicago-area chains and independents. We utilized this data to obtain information on promotional activity. By week we had available the percentage of All Commodity Volume (ACV) of a particular UPC that (1) received in-store display along with a price reduction, (2) was feature advertised along with a price reduction, or (3) was both displayed and feature advertised.

Because feature advertising is a chainwide corporate activity, an individual UPC will either be featured or not featured in all stores during a particular week. Display activity is more discretionary, and except for larger promotions the decision is left up to the store managers. Except for the extreme cases where no stores or all stores display an item, we do not know which stores actually displayed the item. The percent ACV data from IRI provide probabilistic information about the likelihood that an item has received display support. Given the measurement error that is likely to be present in any display variable, we used only information on chainwide feature activity in the demand model.

---

[1]For example, the standard deviation of our ETHNIC variable across stores is .34, whereas the median standard deviation among the census tracts that make up each store is .10. Similarly, the standard deviation of HOUSE_VAL across stores is .33, with a median of .26 within store market areas.

Table 1

CATEGORY AGGREGATES AND ELASTICITY ESTIMATES

Category	Number of UPCs	Number of Items	Basis of Aggregation	Average Category Elasticity	Standard Deviation	Average Own Elasticity
Food Items						
Soft Drinks	619	10	4 manufacturers and 2 size aggregates	−3.18	.39	−2.59
Canned Seafood	180	12	4 brands by water/oil, 4 price tier aggregates	−1.79	.47	−.96
Canned Soup	89	18	13 Campbell's flavor/size aggregates, 5 misc. aggregates	−1.62	.22	−1.66
Cookies	637	13	8 brands (all sizes), 5 manufacturer aggregates	−1.60	.25	−.90
Grahams/Saltines	230	10	5 brands (all flavors) by 2 types	−1.01	.57	−1.46
Snack Crackers	197	15	11 brands (all flavors, sizes), 4 manufacturer aggregates	−.86	.36	−.79
Frozen Entrees	500	12	11 brands (all flavors), 1 miscellaneous aggregate	−.77	.46	−1.65
Refrigerated Juice	108	12	5 orange juice brands by 1–2 sizes, 4 flavor aggregates	−.74	.51	−2.24
Dairy Cheese	367	17	5 brands by 2–5 types, 1 miscellaneous aggregate	−.72	.35	−1.44
Frozen Juice	105	14	9 orange juice brands, 5 flavor aggregates	−.55	.32	−1.95
Cereal	298	21	19 brands (all sizes), 5 type aggregates	−.20	.22	−1.14
Bottled Juice	242	21	10 brands by 1–4 sizes, 1 miscellaneous aggregate	−.09	.26	−1.49
Nonfood Items						
Bath Tissue	57	9	8 brands, 1 aggregate	−2.42	.19	−2.28
Laundry Detergent	303	10	4 brands (all sizes) by 2 forms, 2 form aggregates	−1.58	.21	−1.99
Fabric Softener	140	8	3 brands (all sizes) by 2 forms, 2 form aggregates	−.79	.06	−1.77
Liquid Dish Detergent	178	13	6 brands by sizes, 2 size aggregates	−.74	.29	−1.64
Toothpaste	296	11	4 brands (all flavors) by 2 sizes, 2 size aggregates, kids	−.45	.37	−2.00
Paper Towels	90	12	7 brands by 2 sizes, 2 size aggregates	.05	.52	−1.21

Store Trading Area Data

Marketing Metrics provided us with trading area data for each of the 83 stores. They determine trading areas for all stores with yearly sales volume greater than $2 million, using proprietary models that take into account population density (e.g., urban versus suburban), competition, road conditions, and various regional differences. Marketing Metrics defines a trading area by expanding a polygon around each store location to enclose an area large enough to support the ACV of the store.

Household expenditure functions based on the Bureau of Labor Statistics Consumer Expenditure Survey and Mediamark Research Institute's 1990 Doublebase survey are combined with census block data to estimate the size of the population needed to support the ACV. These trading areas also take into account the presence of competitors who are sharing the grocery expenditure total for a given area as well as geographical barriers such as expressways and rivers and differences in estimated transportation times.

Even though DFF operates in a generally highly competitive environment, there is still a great deal of variation in the nature and extent of competition. In some locations, the DFF and competing stores are located side by side and in other locations the DFF store is not near any major competitor. To measure the extent and nature of the competition, we relied on detailed information about the top ten competitors in the trading area, including distance from the Dominick's store (in miles and estimated driving time minutes), retail format (supermarket, superstore and warehouse outlets, and food/drug combos), and estimated weekly sales volume. This level of detail on the competitive environment is unique in studies of competitive behavior.

Census block data from 1990 provide very extensive demographic information on household size and composition, income, housing, educational attainment, ethnicity, and many other variables. The market area definitions are used

to form weighted averages of the block data within the trading area. The weights decay at different rates for every direction from the store location.

STORE-LEVEL DATA AND AGGREGATION ISSUES

Because our empirical work is based on store-level data, it is important to recognize the advantages and disadvantages of aggregation. On the positive side, aggregation over individual consumers to the store level may tend to average out individual stochastic behavior. Temporary household-specific situational factors (e.g., existing inventory levels affecting response to a deal) will tend to be equalized across consumers, leading to a reduction in systemwide noise. Alternatively, store-level analysis would seem to be counterproductive on the independent variable side, because the high level of aggregation could wash out interesting differences between individual consumers.

In our analysis of store market areas, we must rely on summary statistics to characterize the distribution of key explanatory variables over the consumers in the market area. As in many major metropolitan areas, Chicago has always been a city of many distinct and homogenous neighborhoods; in recent years, out-migration to the suburbs has increased the pattern of residential separation by wealth and ethnicity. Consequently, the variation in consumer characteristics across different store market areas is substantially greater than the variation in characteristics within each market area. This, coupled with the averaging out of individual stochastic behavior, may afford us with a better opportunity to detect relationships between price sensitivity and market area characteristics.

A simple example will help clarify these points further. Consider the relationship between price sensitivity and consumer wealth. With consumer panel data, we could attempt to measure price sensitivity for each consumer and then perform a cross-sectional regression of price sensitivity on a

wealth measure for each household. Given previous findings, we would expect a very weak relationship in this consumer-level data. To reduce measurement noise, we might average price sensitivity over consumers of exactly the same wealth level and regress these averages on our wealth measure. This amounts to averaging the regression error terms vertically at each of some group of wealth points.

Our store-level data divides the consumer population into groups by market area. We compute the average price sensitivity for each market area and regress this on the average wealth for each market area group. This is analogous to averaging the regression errors both vertically (across consumers of the same wealth level) and horizontally (across consumers of different wealth levels in the same market area). Thus, the success of our empirical analysis hinges on the trade-off between reducing noise in the dependent variable and the loss of information through aggregation of the independent variables to market areas.

In the next three sections we will describe our method and results. We adopt a two-step procedure. First, we estimate store-specific price elasticities for each of the 18 product categories.[2] Second, we relate these store/product category elasticities to demographic and competitive variables.

OBTAINING PRICE ELASTICITY ESTIMATES

Obtaining price elasticity estimates for an entire category is a complicated task involving a number of decisions on both aggregation and model specification. In a typical grocery category, supermarkets carry upwards of 250 UPCs. Our approach is to build a detailed demand model at a low level of aggregation to avoid the extreme assumptions and possible aggregation bias that would affect a highly aggregated analysis. This detailed demand model can be used to measure the sales response to changes in the price of individual items and subaggregates or to predict the response of the whole category to a uniform price change across all items in the category.

We concentrate on measurement of the category-level price sensitivity, which is at the core of the retailer's category pricing problem. Currently, most retailers have fairly uniform pricing policies (e.g., they follow or lead the competition), which are not customized to store-specific clientele. Exploring systematic patterns of price sensitivity on the category level can open the possibility of improving profitability by store-specific everyday and promotional pricing. Retailers also may be interested in individual item or brand elasticities, which can be used to predict patterns of differential promotional response.

Demand Model Specification

Our aggregation scheme starts with the total of 4636 UPCs that make up the 18 categories. Even with our 160 weeks of data, it would be difficult to precisely measure 83 × 4636 store-UPC elasticity combinations. Furthermore,

the prices of many UPCs are perfectly correlated, because they are priced and promoted together (e.g., different flavors or forms of the same brand). Therefore, we formed aggregates in each category, consisting of top-selling brands and aggregates of other UPCs on the basis of size, form, flavor, and type. As shown in Table 1, we formed 265 items with an average of 15 aggregates per category (column labeled "Number of Items") from the 4636 UPCs.

The aggregation scheme varied, depending on the level of differentiation and concentration in the category. For example, in the refrigerated juice category, the top ten selling UPCs account for more than 53% of dollar sales volume, whereas in ready-to-eat breakfast cereals the top ten account for less than 17% of sales. In categories with dispersed sales, we aggregated across either sizes and/or flavors/forms to get to a point where the top 10 to 20 items would account for at least 50% of sales.

The choice of model specification also requires a number of trade offs in order to make the problem tractable from an econometric perspective. For example, we might have started with a flexible functional form for the utility function over all brands in each of our 18 categories. We then could derive a huge demand system that would feature hundreds of prices and hundreds of thousands of parameters. Instead, our approach is to specify a simple log-linear demand model in which the log of unit sales for each item is regressed on the log of price of that item and other items in the same category. In addition, we include promotional variables and a lagged sales volume term in each item equation. Thus, we specify m log-linear demand equations for each of the m items in a category. The parameters from this demand system are then used to define a category price elasticity, as described subsequently.

The basic demand system starts with the vector of log unit sales (standardized by size) in store j during week t, q_{jt} and the vector of log prices of each of the m items in each category, p_{jt} (throughout, we denote the logs of variables in lower case). Each element of the vector, q_{jt}, is denoted q_{ijt}, i = 1,..., I, where I is the total number of items in the category; in the equations, i will always denote the index of an item. The price of each of the items in each category is defined as the geometric share average or the Divisia price index of all UPCs that make up that item. For example, in the refrigerated juice category, there are 12 items that are aggregates of the 108 UPCs. For each week and store, we compute the share-weighted average of the log price of each of the UPCs in each item to form the p_{jt} vector, which is a 12 × 1 vector.

For each category, we define a standard log-linear demand system:

$$(1) \quad q_{jt} = \alpha + \tau_j \iota + (N + \Lambda_j)p_{jt} + \Phi q_{j,t-1} + \Delta \, Deal_{jt} + B \, F_{jt} + \varepsilon_{jt}$$

ι is a m × 1 vector of ones, $\Lambda_j = \lambda_j I$, $\Phi = \phi I$, $\Delta = diag(\delta)$, B = diag(β). The α vector allows for item-specific intercepts, and the τ_j parameter is a store-specific intercept. $Deal_{jt}$ is a vector of dummy variables that indicate whether there is a temporary price reduction or an in-store coupon. F_{jt} is a vector of feature indicator variables obtained from IRI's InfoScan sample of DFF stores in the Chicago area. The model

---

[2]An alternative approach would a one-step procedure in which the elasticity coefficients in the demand model in (1) are made functions of the demographic variables. To implement a one-step strategy, we would need to make specific distributional assumptions regarding the store elasticity random component or asymptotic arguments which require a large number of categories. Our approach is a nonparametric fixed effects one, which estimates a store elasticity component in the first step.

in (1) is estimated on the first 80 weeks of our store data, re-serving the remaining 80 weeks for model validation.

The demand system in (1) allows for a full pattern of cross elasticities, as captured by the elements of the N matrix, N = [$\eta_{ii'}$], along with a lagged value of the dependent variable that is introduced to accommodate serial correlation introduced by forward buying or inventorying behavior. The Λ_j matrix allows for a store-specific effect on the own elasticities. The model in (1) makes three basic sets of restrictions on the category demand model. We allow only the own elasticity parameters ($\eta_{ii'} + \lambda_j$) to vary across stores, while we restrict the cross-elasticity parameters (N) so they are the same across stores.

Feature and deal effects are allowed to be item-specific but not store-specific. The lagged sale effect is the same across items in the same category. The price elasticity models fit the data very well, with R^2 ranging from .76 to .93. Large feature effects are observed in most categories. To validate this modeling approach, we experimented extensively with alternative formulations that are, to varying degrees, less restrictive than the model in (1). Our model performs well relative to these less restrictive models, as measured by both in-sample and out-of-sample yardsticks of performance.[3]

Category-Level Price Elasticities

The price response parameters in (1) can be used to predict response to a wide variety of price changes on both the item and category level. Since our focus is on the retailer's category pricing problem, we derive a category elasticity measure by computing the category volume response to a proportionate change in all prices in the category, holding the promotional policy variables constant. For a particular store, the demand system (1) can be written as

$$q_j = a + \Gamma_j p_j$$

The intercept a includes the feature, deal, and lagged q variables, which are not changed in the price response partial derivative, and $\Gamma_j = N + \Lambda_j$, which is the store-specific price coefficient matrix. Because the demand system is written in logs, our category elasticity measure can be computed by adding a constant to the vector of log prices, p + hι, and observing its effect on log volume in the category.

Total category unit volume is written as $V(p) = \Sigma exp(q_i)$ $= \Sigma exp\{a_i + \gamma_{ij}'p\}$, where γ_{ij} is the ith row of Γ_j. The category elasticity for store j is defined as the percentage change in the category volume produced by a uniform 1% increase in the prices of all items in the category. In differential terms, we must take the partial derivative of lnV with respect to h, where h is the constant of proportionality; we increase p to p' = p + hι. We are considering the local or derivative measure, so we must take the limit of this derivative as h → 0.

$$(2) \qquad \eta_{cj} = \frac{\partial}{\partial h} \ln V(p + h\iota)\big|_{h=0} = \sum_{i=1}^{m} \frac{Q_{ij}}{V} \gamma_{ij}'\iota = w_j'\Gamma_j\iota$$

w_j is the vector of volume shares, $w_{ij} = Q_{ij}/V$, where Q_{ij} is the unit volume for item i in store j. The category price elasticity measure in (2) provides an estimate of the expected percentage change in category unit volume for a 1% uniform increase in the prices of all the items in the category. For each category (c = 1, ..., C) and each store (j = 1, ..., J), we use (2) to compute a category elasticity, η_{cj}. We should note that these are short-run elasticities; the long-run elasticity would be scaled up by the factor $1/(1-\phi)$.

Table 1 presents descriptive information on the level and dispersion of the category elasticity estimates. The categories are sorted first into food and nonfood items and then ranked on the basis of the size of elasticities. The average category elasticity is -1.06, and the average standard deviation across stores in the same category is .33, indicating that there is a great deal of variation across stores within the same category.

Table 1 presents the average own price elasticity in addition to the category elasticity, which is driven by the degree of substitutability among categories in the same store and between competing stores. Substitution or switching between brands in the same category has a small effect on the category elasticity (it can have some effect if the volume of purchases change). This suggests that the category elasticity should be smaller than the item or brand elasticity, as shown in Table 1, which is the case in 13 out of the 18 categories. Furthermore, for those categories in which there is intense store competition and wider retail distribution (e.g., drug, convenience stores, and discount stores), we should expect higher category elasticities driven by substitution across stores. This is the case in the soft drink and bath tissue categories.

Figure 1 is a map of the Chicago area with each of the DFF store locations marked with a dot. Around each store location is a circle whose radius is proportional to the size of the price elasticity estimates for the soft drink category. Considerable variation in the size of elasticities, clustering of similar size elasticities, and smooth transition from one geographic area to the next are apparent in the figure. The challenge now is to relate this variation in elasticities to market area characteristics.

RESULTS FOR INDIVIDUAL CATEGORIES

Given the category elasticity estimates, we examine the relationship between these estimates and measures of consumer and competitive characteristics. A regression relationship between the elasticity estimate, n_{cj}, and the independent variables is postulated.

$$(3) \qquad n_{cj} = x_j'\beta_c + \varepsilon_{cj} \qquad \varepsilon_{cj} \sim iid\ N(0, \sigma_c)\ c = 1, 2, ... 18$$

---

[3]Without restrictions on the variation in cross-elasticity patterns, we would be faced with the problem of estimating $m^2 \times J$ price parameters (where J is the total number of stores) versus the $m^2 + J$ parameters employed in (1). To assess the validity of these restrictions, we also estimated a completely unrestricted model that allows the cross-elasticities to vary across stores. We use out-of-sample predictive validation and the Schwarz (1978) model selection criterion to compare the restricted and unrestricted models. The unrestricted models have between 30 and 60 times the number of parameters as the restricted model in (1) and, as might be expected, they show a somewhat smaller in-sample MSE. The lower in-sample MSE is almost entirely attributable to a fuller set of brand-store intercepts; freeing the restrictions on the cross-price elasticity terms results in little improvement in fit. However, the out-of-sample predictive performance of the unrestricted model is much inferior to the restricted model. The restricted model shows an average 55% reduction in out-of-sample MSE, with a minimum of 14% and a maximum of 97%. This suggests that there is a great deal of sampling variability in the parameter estimates in the unrestricted model. The Schwarz (1978) model selection criterion also favors the restricted model.

There are 18 category-level regressions each with 83 store observations on consumer and competitive characteristics (these are in the vector x_j). Because the n_{cj} are based on regression coefficient estimates (see (2)), they could be heteroskedastic over stores in the same category. This regression equation assumes that the estimates are homoskedastic within a category and heteroskedastic across categories. To check this assumption, we computed the standard errors of the n_{cj} using standard regression theory and (2). We found very little variation in these standard errors across stores for each of the 18 categories, justifying our error specification in (3). We now turn to the construction and selection of independent variables.

Selection of Independent Variables

Because of the comprehensive amount of background information available for each trading area, we spent considerable effort identifying a parsimonious model of price sensitivity that contained both consumer and competitive characteristics. Our intent was not so much to find the one true model but to identify factors consistent with the household production and economics of information approaches. Relating specific demographic variables to economic concepts is difficult. For example, a number of demographic variables could be related to wealth or to the opportunity cost of time. We use multiple variables as proxies for key concepts and anticipate that some collinearity will exist between the demographic variables. The final model that we report here contained 11 predictor variables.

Consumer characteristics: Seven of the predictor variables were consumer characteristics. The percentage of the population over 60 years of age (ELDERLY), the percentage of the population with a college education (EDUC), and the percentage of households with five or more members (FAM_SIZE) relate to opportunity costs. Elderly people and larger households were expected to be more price sensitive, leading to negative relationships with price elasticity. The log of median income (INCOME) and the percentage of the homes with a value greater than $150,000 (HOUSE_VAL) are related to income constraints on purchasing behavior. We also included the percentage of women who work (WORK_WOM). If this variable represents the higher opportunity costs of working women, then we would expect it to be positively related to price elasticity. If, however, many working women face budget constraints, then the sign might reverse. We tried to isolate demographics that might capture differential levels of storage and transportation costs, but we could find no systematic relationships to price sensitivity.

In addition, we included the percentage of consumers who were black and Hispanic (ETHNIC) as an independent variable. This variable is best regarded as an intermediate construct that captures underlying characteristics such as certain patterns of income, household composition, and personal wealth for which economic theory makes price response predictions.

We experimented with model specifications in which the ETHNIC variable was replaced by associated measures (e.g., percentage below the poverty line, unemployment levels, telephone ownership, percentage of singles); however, ETHNIC captured something additional, so we retained the
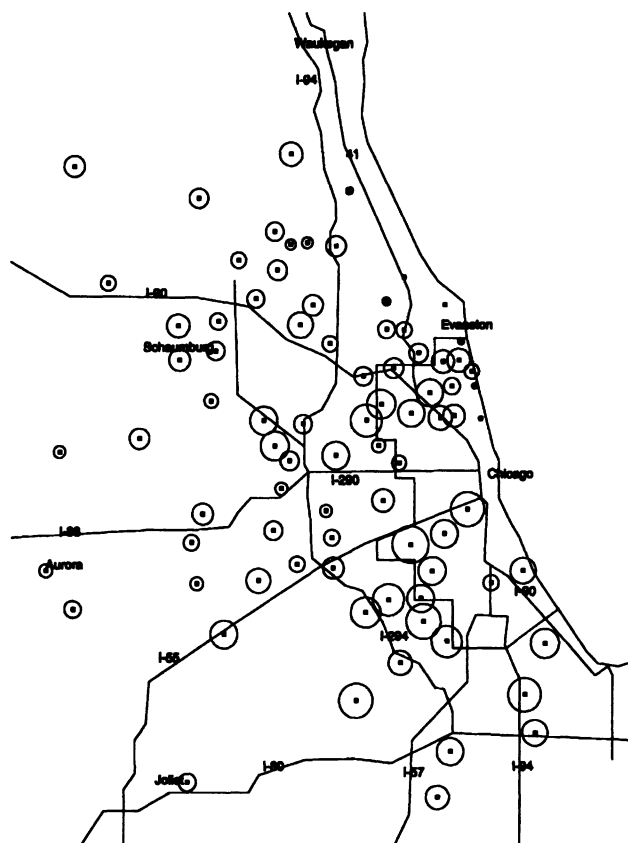
variable. In addition, the ETHNIC variable has obvious value as a predictor in the event that this analysis was used to forecast price sensitivity at locations for which we do not have detailed scanner data.

Competitive characteristics: Four of the predictor variables were competitive characteristics. We divided the competition into two sources: traditional supermarkets and warehouse or superstore operations. Distance in miles and driving time were closely related. We calculated the average distance in miles to the nearest five supermarket competitors (SUPER_DIS) and the distance to the nearest warehouse operation (WARE_DIS). Distance in urban areas was scaled by a factor of two to reflect greater congestion and density. We also calculated the sales volume (a proxy for store size) of each store relative to both the supermarket (SUPER_VOL) and warehouse (WARE_VOL) competitors.

Examination of the distribution of the independent variables across each of the 83 stores shows that there is considerable variation in both the demographic and competitive characteristics. For example, there are DFF stores in market areas in which less than 5% of the adult population is college-educated, whereas other locations have more than 50% of college-educated consumers. Figure 2 shows the difference in the EDUC variable on the map of DFF locations. Some DFF stores are located right next to both supermarket and warehouse competition, and others are located as far as

Figure 2
PERCENTAGE COLLEGE EDUCATED BY DFF LOCATION
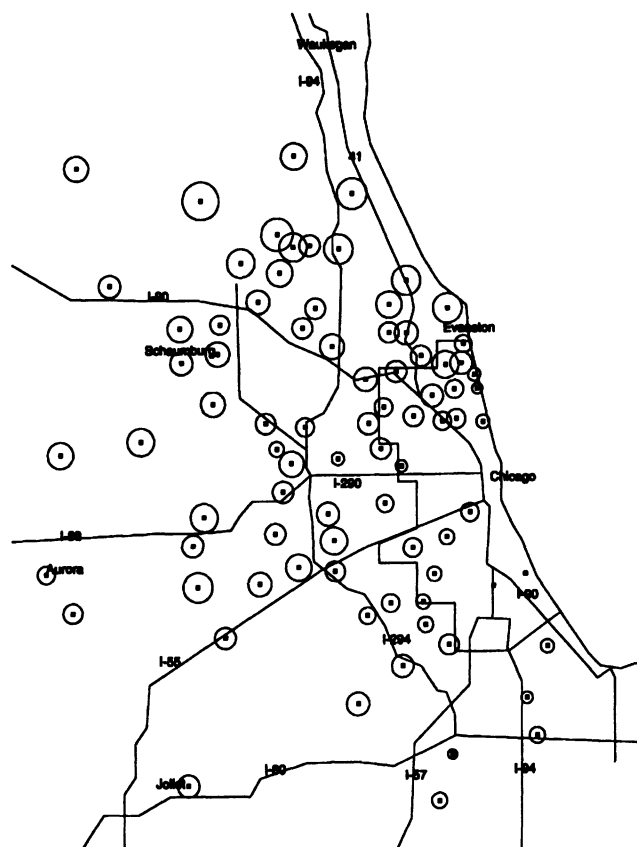
18 miles from warehouse competition and 4 miles from major supermarket competition. In addition, most of the intercorrelation between the 11 independent variables is below .5 in absolute value, with the exception of a .89 correlation between HOUSE_VAL and EDUC.

Results of Category Regressions

The 18 category regressions of elasticities on this set of independent variables are listed in Table 2. The categories are listed in alphabetic order across the columns of the table. Below each coefficient is the standard error, and the bottom two rows give the adjusted R^2 and standard error of the regression. The last column displays the variance inflation factors (VIF) for each independent variable (see Weisberg 1985 for a definition of the VIF).

Note that the VIF depends only on the independent variables, which are the same in each of the 18 regressions. The regressions have an average adjusted R^2 of .67 (median, .78), ranging from a low of .34 for toothpaste to a high of .86 for frozen entrees. The regressions show a remarkably good fit, especially in light of previous attempts to explain variations in price response. In addition, our success in explaining variations in price elasticity measures suggests that the measurement error in these elasticities is low relative to their store-to-store variation.

We now turn to an analysis of the direction of the effects of each independent variable. In interpreting these coefficients, it is important to remember that the dependent variable is a negative number. A positive coefficient indicates that as the associated independent variable increases, the price elasticity moves closer to zero. These coefficient distributions can be summarized as follows:

- The EDUC and HOUSE_VAL variables reduce price sensitivity, as evidenced by the overwhelming majority of positive coefficients.
- The ETHNIC, FAM_SIZE, and WORK_WOM variables increase price sensitivity for the most part.
- The INCOME and ELDERLY variables are a mixed bag, with almost equal numbers of positive and negative coefficients.
- WARE_VOL increases price sensitivity as expected, and WARE_DIS reduces price sensitivity.
- The SUPER_DIS and SUPER_VOL variables have weak and mixed effects.

To assess the potential problems associated with collinearity, we computed variance inflation factors for each of the independent variables. The only large VIFs were associated with the EDUC and HOUSE_VAL variables, reflecting their high degree of intercorrelation. Even these VIFs were around 7.0, which shows that there is still considerable independent variation in these variables. All other VIFs are 4 or below, with most below 3. Thus, the diversity in the DFF market area allows us to isolate effects that are difficult to find in the relatively homogenous cities in which scanner panel data is usually collected (e.g., Sioux Falls, SD, and Springfield, MO, for ERIM data and Marion, IN, and Rome, GA, for the IRI academic data sets).

Although Table 2 provides information about the direction of the effects and the statistical strength of the evidence, it does not directly address the substantive impact of the variables. To better gauge the relative importance of demographic versus competition variables, Table 3 presents the results of a series of four sets of regression equations. It starts in column 2 with the root mean squared error (RMSE) for the base model, which is a simple category-level mean. The rest of the columns present the ratio of RMSE from regressions with different sets of independent variables to this base model. The addition of the demographic variables to the base model results in a large decrease in RMSE (the column marked Demographic Variables). On the other hand, the competition variables add little either incrementally over the demographic variables (Demographic | Competition Variables) or compared to the base model alone (Competition Variables). This is an interesting result, given retailers' typical focus on their competition.

Despite the large qualitative differences between the product categories, the regression coefficients consistently cluster around positive or negative values for many of the independent variables. However, there are a few exceptions; for example, although most of the coefficients for the EDUC variable are positive and most of the coefficients for the ETHNIC variables are negative, there are a few significant coefficients of the opposite sign.

For other independent variables, such as the ELDERLY variable, there are a number of significant positive and negative coefficients. The elderly may display a preference for

Table 2
INDIVIDUAL CATEGORY REGRESSION RESULTS

Independent Variables	Bath Tissue	Bottled Juice	Canned Seafood	Canned Soup	Cereal	Cookies	Grahams/ Saltines	Dairy Cheese	Fabric Softener	Frozen Entree	Frozen Juice	Laundry Detergent	Liquid Dish Detergent	Paper Towels	Refrigerated Juice	Snack Crackers	Soft Drinks	Tooth- paste	VIF
ELDERLY	.341 (.539)	1.978 (.452)	1.119 (.463)	2.136 (.833)	-.942 (.399)	-.70 (.436)	-1.660 (.824)	.635 (.586)	.347 (.236)	1.398 (.671)	-1.405 (.777)	-2.158 (.557)	-.606 (.648)	-1.271 (1.360)	.190 (.849)	-.577 (.656)	.920 (.899)	-1.205 (1.146)	4.82
EDUC	.365 (.399)	.630 (.343)	.860 (.334)	1.830 (.617)	.051 (.296)	.819 (.323)	.558 (.610)	1.646 (.434)	-.206 (.174)	.624 (.497)	.433 (.576)	-.535 (.412)	.466 (.480)	-.645 (1.007)	.289 (.628)	1.992 (.486)	2.774 (.666)	1.689 (.848)	7.79
ETHNIC	-.121 (.152)	.424 (.130)	-.074 (.127)	-.498 (.235)	-.754 (.112)	-.152 (.123)	-.566 (.232)	-.081 (.165)	.325 (.066)	.133 (.189)	.015 (.219)	-.241 (.157)	-.759 (.183)	-.631 (.383)	-.487 (.239)	-1.677 (.185)	.044 (.253)	.273 (.323)	3.35
INCOME	-.257 (.134)	-.600 (.115)	-.453 (.113)	-.303 (.208)	.074 (.099)	-.233 (.108)	.817 (.205)	-.170 (.146)	.056 (.059)	.227 (.167)	-.148 (.194)	-.063 (.139)	.022 (.161)	.702 (.339)	.176 (.211)	-.776 (.163)	-.517 (.224)	.163 (.285)	5.81
FAMILY_SIZE	-.745 (.964)	-1.658 (.829)	-.023 (.809)	1.285 (1.492)	.884 (.715)	-1.764 (.780)	-1.882 (1.476)	-.126 (1.049)	.597 (.422)	-1.906 (1.201)	-2.877 (1.392)	-2.056 (.997)	-.703 (1.161)	-2.587 (2.435)	-2.439 (1.520)	.505 (1.175)	-.591 (1.609)	.987 (2.052)	3.71
WORK_WOM	-1.475 (.625)	-.339 (.537)	.464 (.524)	.100 (.967)	-.556 (.463)	-.697 (.505)	-.609 (.956)	.371 (.680)	-.255 (.273)	.849 (.778)	-1.365 (.902)	-.340 (.646)	.299 (.752)	-1.118 (1.578)	-.386 (.985)	-.346 (.761)	.653 (1.043)	-.419 (1.330)	4.49
HOUSE_VAL	.136 (.171)	.394 (.147)	.628 (.144)	1.172 (.265)	.273 (.127)	.605 (.139)	.727 (.262)	.605 (.186)	.079 (.075)	1.300 (.214)	.819 (.248)	.539 (.177)	.233 (.206)	.796 (.433)	1.344 (.270)	.152 (.209)	.127 (.286)	-.151 (.365)	6.59
WARE_DIS	.013 (.005)	-.003 (.005)	-.010 (.005)	-.000 (.008)	.008 (.004)	.001 (.004)	-.004 (.008)	.009 (.006)	-.004 (.002)	-.006 (.007)	.019 (.008)	.004 (.006)	.006 (.007)	.007 (.014)	.010 (.009)	-.003 (.007)	.019 (.009)	.009 (.012)	1.78
WARE_VOL	-.022 (.042)	-.049 (.036)	.010 (.036)	-.031 (.066)	-.114 (.031)	-.045 (.034)	-.093 (.065)	-.100 (.046)	.010 (.019)	.028 (.053)	.030 (.061)	-.021 (.044)	-.087 (.051)	-.184 (.107)	-.081 (.067)	-.104 (.052)	-.185 (.071)	-.130 (.090)	1.75
SUPER_DIS	-.042 (.026)	-.003 (.022)	-.003 (.021)	.041 (.040)	.001 (.019)	.019 (.021)	-.014 (.039)	-.007 (.028)	-.004 (.011)	.054 (.032)	-.008 (.037)	.042 (.026)	-.043 (.031)	.003 (.065)	-.038 (.040)	.033 (.031)	.006 (.043)	.185 (.054)	1.43
SUPER_VOL	.063 (.114)	.017 (.098)	-.193 (.096)	-.229 (.177)	-.045 (.085)	-.055 (.093)	-.072 (.175)	.043 (.124)	.034 (.050)	-.263 (.142)	-.293 (.165)	.031 (.118)	-.057 (.138)	-.325 (.289)	-.151 (.180)	.210 (.139)	.385 (.191)	-.108 (.243)	2.20
Intercept	.765 (1.307)	5.990 (1.124)	2.576 (1.096)	.195 (2.022)	-.592 (.969)	1.120 (1.057)	-9.043 (2.000)	.363 (1.421)	-1.449 (.572)	-4.110 (1.628)	1.692 (1.886)	-.305 (1.351)	-.768 (1.573)	-6.180 (3.301)	-2.481 (2.060)	7.284 (1.592)	1.250 (2.181)	-2.531 (2.781)	
RMSE	.142	.122	.119	.220	.105	.115	.217	.155	.062	.177	.205	.147	.171	.359	.224	.173	.237	.302	
AdjR²	.417	.782	.698	.782	.771	.782	.852	.804	.450	.854	.595	.492	.646	.524	.810	.774	.628	.339	

Table 3
RELATIVE RMSE BY MODEL SPECIFICATION

Category	Base RMSE	Constant	Demographic Variables	Competition Variables	Demographic/Competition Variables
Bath Tissue	.187	1.0	.78	.87	.76
Bottled Juice	.263	1.0	.46	.87	.46
Canned Seafood	.474	1.0	.47	.94	.46
Canned Soup	.218	1.0	.56	.93	.55
Cereals	.221	1.0	.55	.83	.48
Cookies	.247	1.0	.47	.90	.46
Grahams/Saltines	.569	1.0	.38	.84	.38
Dairy Cheese	.351	1.0	.45	.86	.44
Fabric Softener	.084	1.0	.74	.94	.74
Frozen Entrees	.466	1.0	.39	.93	.38
Frozen Juice	.324	1.0	.67	.91	.63
Laundry Detergent	.207	1.0	.71	.92	.71
Liquid Dish Detergent	.289	1.0	.60	.86	.59
Paper Towels	.523	1.0	.71	.91	.69
Refrigerated Juice	.517	1.0	.44	.89	.43
Soft Drinks	.391	1.0	.63	.85	.61
Snack Crackers	.367	1.0	.48	.83	.47
Toothpaste	.374	1.0	.89	.92	.81
Average	.338	1.0	.58	.89	.56

some product categories, such as condensed soup, which may counterbalance other factors that would lead to greater price sensitivity.

It is unreasonable to expect all categories to display the same pattern of coefficients. There is tremendous variation in the size, level of aggregation, type of product, inventory patterns, and degree of complementarity or substitutability with other products across the 18 categories. Furthermore, we have estimated 216 regression coefficients in the category regressions and it is possible to obtain a number of significant coefficients of the opposite sign from the population value, even when testing at the 5% level.

Therefore, we conducted an exploratory principal component analysis to assess commonality across categories in the elasticity estimates. The first principal component of the 18 × 18 correlation of the category elasticities across the stores explains some 54% of the total variation. Any one of the other factors explains little of the total variation. The first eigenvector weights every category except one with positive weights, suggesting that there is a strong common component that might be interpreted as an overall store elasticity.

The common patterns in regression coefficients across categories naturally leads to consideration of methods for pooling the information across categories, both to obtain more precise estimates of the common pattern and to better summarize the central tendencies in the data.

In the next section, we explore pooling methods for combining information across categories.

POOLED ANALYSIS

All pooling strategies rely on a set of assumptions that tie together each of the individual category regressions. We start by introducing notation and error assumptions for the system of category regressions that form a multivariate regression system.

$$(4) \qquad y_1 = \alpha_1 + X\beta_1 + \varepsilon_1$$

$$\varepsilon' = (\varepsilon_1', ..., \varepsilon_C') \sim MVN(0, \Lambda \otimes I_n)$$

$$\Lambda = diag(\sigma_1^2, ..., \sigma_C^2)$$

$$y_C = \alpha_C + X\beta_C + \varepsilon_C$$

The specification in (4) allows for category-specific intercepts. y_c is a N (number of stores) × 1 vector of elasticities for the cth category expressed in terms of deviations from the mean category elasticity. X is the N × k matrix of values of the k independent variables, β_c is the cth category slope coefficient vector, and ε_c is the N × 1 vector of error terms for the cth category. In our case, there are C = 18 categories, k = 11 independent variables, and N = 83 stores. Note that our regression specification has a separate intercept for each category; this is true even for the random coefficient approach discussed subsequently.

This means that we seek only to explain the variation in elasticities across stores. We do not attempt to identify factors that could explain differences in mean elasticities *across* categories. Admittedly, understanding differences in the level of elasticities across categories is an interesting topic, though it is not our focus here.

We make two key assumptions about the correlation structure of the error terms. First, we assume that errors are independent across stores within a given category, that is, that $\varepsilon_c \sim MVN(0, \sigma_c^2 I_n)$. This is reasonable because of our careful selection of relevant independent variables. Second, we assume that errors across categories for the same store are independent. Our analysis of the correlation matrix of category-level regression residuals justifies this second assumption.

One standard approach to pooling information across categories would be to restrict some or all of the regression coefficients so they were the same across each of the C cate-

gory regressions in (4). The evidence reported in section 6 suggests that such severe pooling restrictions are not warranted. We might expect that the coefficients would display consistent patterns in sign, but we see no a priori theoretical reasons why the coefficients should have the same magnitude across categories. To formally test the pooling restriction, $H_0: \beta_1 = ... = \beta_C$, we computed likelihood ratio tests of this restriction in the system (4). The restriction is rejected at the .001 level.

It is also possible to interpret the pooled results in the context of a random coefficient model, in which each of the category coefficient vectors is viewed as a draw from a super-population distribution; that is, β_c are distributed iid with mean $E[\beta_c] = \bar{\beta}$ and variance, $Var(\beta_c) = V_\beta$. To characterize the central tendency or commonality among the categories, we would like to make an inference about the mean of this random coefficient distribution. The pooled regression stacks up the C regressions in (4) into one large regression system with common slope coefficients. $y = X\beta + u$, where y is a CN × 1 vector of elasticities, X is a CN × (C + k) matrix of independent variables, β is the vector of category intercepts, and k is the common slope coefficients. The least squares estimates of the common coefficient vector in the pooled regression approach is a consistent estimate of $\bar{\beta}$. However, if one subscribes to the random coefficient view, then the error terms in the pooled regression will display a special form of heteroskedasticity. In the standard random coefficient literature (see discussion and literature review in Judge et al. 1985, Chapter 13), various methods of estimating the variance components in the error structure are combined with a feasible GLS approach to produce asymptotically efficient estimates of β.

Our approach is to avoid specific assumptions regarding the form of the heteroskedasticity induced by the random coefficient interpretation and use instead the general heteroskedastic estimator of the variance covariance matrix of the least squares estimator proposed by White (1980). Thus, we use ordinary least squares and compute adjusted standard errors that are asymptotically justified.

It is important to note that the asymptotic arguments required for use of our adjusted standard errors necessitate that the number of observations in the pooled regression (CN = 83 × 18 = 1494) to be large. The standard random coefficient approaches pursued in the econometrics literature are asymptotic in the number of categories. A more formal analysis that does not require asymptotic arguments of any sort can be obtained by the use of Bayesian hierarchical models. Montgomery and Rossi (1993) conduct a hierarchical analysis using Gibbs sampling, which provides results very similar to those presented here.

Table 4 presents the pooled estimates of $\bar{\beta}$ along with the heteroskedastic-consistent standard errors and 90% confidence intervals. The pooled analysis reinforces the conclusions from individual category regressions. On average across categories, the ETHNIC, FAM_SIZ, and WARE_VOL variables have negative coefficients, leading to high price sensitivity for higher values of these variables. The EDUC, HOUSE_VAL, and WARE_DIS variables have positive coefficients.

Table 4
RESULTS POOLED ACROSS CATEGORIES

Variable	$\bar{\beta}$ (Standard Error)	90% Confidence Interval
ELDERLY	−.082 (.25)	(−.50, .33)
EDUC	.76 (.17)	(.48, 1.0)
ETHNIC	−.27 (.10)	(−.43, −.11)
INCOME	−.071 (.076)	(−.20, .054)
FAMILY_SIZE	−.84 (.50)	(−1.7, −.0018)
WORK_WOM	−.29 (.28)	(−.75, .17)
HOUSE_VAL	.54 (.071)	(.42, .66)
WARE_DIS	−.00042 (.00024)	(−.00083, .00003)
WARE_VOL	−.065 (.017)	(−.093, −.037)
SUPER_DIS	.012 (.012)	(−.0077, .032)
SUPER_VOL	−.056 (.048)	(−.13, .023)

IMPLICATIONS FOR RETAIL PRICING

In this section, we explore the relevance of our results for both the everyday and promotional pricing policies of the retailer. Dominick's current everyday pricing policy allows for some customization to the store level, with the assignment of stores to one of three price zones. The price zones essentially dictate the everyday pricing of all items in the store, with the promotional prices determined in a uniform manner across the chain. Our results suggest that both their price zones and the reliance on uniform promotional policies can be improved.

The three DFF price zones are defined almost entirely by the extent of nearby competition. The lowest price zone is a warehouse-fighter zone, which is aimed at achieving closer parity with large EDLP warehouse operations. Consumer demographic characteristics figure only minimally in the determination of the price zones. To explore the potential for improvement in the existing everyday pricing policy, we construct a table showing the relationship between store membership in each of the three price zones and the level of price sensitivity. We compute a share-weighted average of each of the category elasticities for each store and divide the stores into the top quartile of price sensitivity, the middle 50%, and the bottom quartile (high, medium, and low in the table below).

Table 5 shows no relationship between price zone and price sensitivity (chi-squared test for independence has $p = .28$ and Spearman rank correlation = .20). This opens the possibility for an improved pricing policy in which the more price-sensitive stores have lower everyday prices. Hoch, Drèze, and Purk (1993) discuss the results of experiments in

Table 5
DFF PRICE ZONE SENSITIVITY

	Zone 1 Low Price	Zone 2 Medium Price	Zone 3 High Price	Total
High Price Sensitivity	2	14	4	20
Medium	6	25	11	42
Low	1	10	10	21
Total	9	49	25	83

the DFF chain that confirm the short-run profitability of such a strategy.

Perhaps the most immediate benefit that our results provide the retailer is a method to more effectively use a promotional budget. Currently, DFF conducts a chainwide promotional strategy in which prices are lowered by a uniform percentage across all stores in the chain. The purpose of these temporary price cuts is to stimulate sales of the item. It is common for the manufacturer to reimburse DFF on the basis of increased sales of an item.

If we view the narrow objective of a price promotion as to achieving a given percentage increase in sales, then it is clear that our price sensitivity estimates can be used to achieve a given promotional lift at a lower total cost. This nonuniform policy exploits the opportunities for store-level price discrimination. Because DFF gets more bang for a given price reduction in the price-sensitive stores than in the relatively price-insensitive stores, a simple strategy for reducing promotion costs would be to have smaller price cuts in the highly sensitive stores coupled with large cuts in the insensitive stores. The benefits of utilizing a customized promotional strategy will depend primarily on the variation in store price elasticities as well the magnitudes of the item price elasticity.

To illustrate how large these benefits might be, let us first consider an item in the refrigerated juice category that has both high variation in store price elasticities (standard deviation of .51) combined with a high level of elasticity (-2.24). We select the Tropicana 64-ounce orange juice item, which has one of the highest market shares of our aggregates in this category. To achieve an expected increase of 50% in unit sales over the whole chain, DFF's uniform promotional strategy would require a 10.84% price cut at a cost measured by reduced profits of $570 per week. On the other hand, a customized promotional strategy that adjusts the amount of the price reduction for each store, depending on the price elasticity, would have a cost savings of 15%. Cost savings from customized promotional strategies would be minimal in other categories that show low variation in price sensitivity across stores. For example, in the fabric softener category, a customized strategy for the promotion of the Downy sheets item would result in a cost savings of only about 1%.

We do not mean to suggest that the current policies of DFF are irrational or suboptimal. The optimality of current policies should be judged relative to the information processing and analytical constraints under which DFF operates. Even though the scanner data used in this analysis is available to most major grocery retailers, the analytical tools and software and hardware technology are not readily available or well appreciated. We expect that competitive pres-sures will force retailers and manufacturers to adopt a more database-driven approach to pricing.

CONCLUSIONS

As the consumer packaged goods industry grows more competitive, both retailers and manufacturers are investing substantial resources in developing micromarketing strategies in an effort to capture new economic rents from customized policies. These efforts are predicated on the assumption that there are systematic and identifiable differences in consumer behavior across store locations.

Our analysis provides support for this view by demonstrating that price sensitivity measures are systematically related to characteristics of the consumers in the market area and the competitive environment. Typically, more than two thirds of the store-to-store variation in elasticities can be explained by 11 demographic and competitive variables. The direction of the relationship between characteristics and price sensitivity follows those predicted by a simple economic framework. The results are summarized as follows:

(1) More educated consumers have higher opportunity costs, so they devote less attention to shopping and therefore are less price sensitive.

(2) Large families spend more of their disposable income on grocery products, and therefore they spend more time shopping to garner their increased returns to search; they are also more price sensitive.

(3) Households with larger, more expensive homes have fewer income constraints, so they are less price sensitive.

(4) Black and hispanic consumers are more price sensitive.

(5) Store volume relative to the competition is important, suggesting that consumers self-select for location and convenience or price and assortment.

(6) Distance from the competition also matters. Isolated stores display less price sensitivity than stores located close to their competitors. Distance increases shopping costs.

Our results suggest that the characteristics of the competitive environment are not all that important as determinants of store price sensitivity (see Table 3). It is reasonable to ask why this is so. We could be utilizing inadequate measures of competition. However, we experimented with numerous formulations of competition with no success. Moreover, to our knowledge, our competitive data is more comprehensive than anything that has been used previously.

It is also possible that error in the competitive variables induces bias and reduces their predictive power. No doubt there is error in our measures of competition, but probably no greater than the error found in the consumer variables based on census data. It may also be that the market is already in price equilibrium and as a result there are no returns for the consumer to search for, because retailers have already adjusted their prices to their consumers and the competition. We find no evidence to support this contention. Across categories, the average correlation between weekly competitor prices at the sku level is only .32. Although there is price matching in terms of everyday prices, promotional pricing is not coordinated. Therefore, sizable gains from consumer price search are possible.

Another explanation for the failure of competitive variables may be inferred from the work of Bresnahan and Reiss (1991), who find that once a market is served by more than

three firms, the monopoly rents have virtually disappeared. Thus, although it may seem that there is a good deal of difference in the competition variables, it may be that all DFF locations face an extremely competitive environment.

Although a metropolitan area like Chicago has few geographically isolated stores (as are found in a rural area), there are some DFF locations on the south side of the city with very little competition. These stores are in economically disadvantaged urban areas, in which few retailers are willing to locate. However, despite little competition, these stores are among the most price sensitive in the chain.

Our results cast some doubt on the optimality of the current pricing policies of grocery retailers. All the major retailers in Chicago divide their stores into a small set (typically less than five) of price zones. These pricing practices are driven almost exclusively by local competition. On an everyday basis, shelf prices will be at most a few pennies different than the local competition. Although it does make sense to charge different prices at different locations, depending on the extent of competition, our analysis suggests that consumer characteristics as well as the extent of competition are important and should inform the pricing decision.

REFERENCES

Bawa, Kapil and Robert Shoemaker (1987), "The Coupon-Prone Consumer: Some Findings Based on Purchase Behavior Across Product Classes," *Journal of Marketing*, 51 (October), 99–110.

——— and ——— (1989), "Analyzing Incremental Sales From a Direct Mail Coupon Promotion," *Journal of Marketing*, 53 (July), 66–78.

Becker, Gary (1965), "A Theory of the Allocation of Time," *Economic Journal*, 75, 493–517.

Blattberg, Robert, Tom Buesing, Peter Peacock, and Subrata Sen (1978), "Identifying the Deal Prone Segment," *Journal of Marketing Research*, 15 (August), 369–77.

Bolton, Ruth (1989), "The Relationship Between Market Characteristics and Promotional Price Elasticities," *Marketing Science*, 8, 153–69.

Bresnahan, Timothy and Peter Reiss (1991), "Entry and Competition in Concentrated Markets," *Journal of Political Economy*, 99, 977–1009.

Carlson, John and Robert Gieseke (1983), "Price Search in a Product Market," *Journal of Consumer Research*, 9 (March), 357–65.

Elrod, Terry and Russell Winer (1982), "An Empirical Evaluation of Aggregation Approaches for Developing Market Segments," *Journal of Marketing*, 46 (Fall), 65–74.

Frank, Robert, William Massy, and Yoram Wind (1972), *Market Segmentation*. Englewood Cliffs, NJ: Prentice-Hall.

Goldman, Arieh and J. K. Johansson (1978), "Determinants of Search for Lower Prices: An Empirical Assessment of the Economics of Information Theory," *Journal of Consumer Research*, 5 (December), 176–86.

Hoch, Steve, Xavier Drèze, and Mary Purk (1993), "Data Driven Micro-Marketing: An Analysis of EDLP and Hi-Lo Pricing Strategies," micromarketing research project, Graduate School of Business, University of Chicago.

Judge, George et al (1985), *The Theory and Practice of Econometrics*. New York: John Wiley and Sons, Inc.

Kumar, V. and Robert Leone (1988), "Measuring the Effect of Retail Store Promotions on Brand and Store Substitution," *Journal of Marketing Research*, 25 (May), 178–85.

Marvel, Howard (1976), "The Economics of Information and Retail Gasoline Price Behavior: An Empirical Analysis," *Journal of Political Economy*, 84, 1033–1060.

Maurizi, Andrew and Timothy Kelly (1978), *Prices and Consumer Information: The Benefits From Posting Retail Gasoline Prices*. Washington, DC: American Enterprise Institute.

Marmorstein, Howard, Dhruv Grewel, and Raymond Fishe (1992), "The Value of Time Spent in Price-Comparison Shopping: Survey and Experimental Evidence," *Journal of Consumer Research*, 19 (June), 52–61.

Mischel, Walter (1984), "Convergences and Challenges in the Search of Consistency," *American Psychologist*, 39, 351–64.

Montgomery, David (1971), "Consumer Characteristics Associated With Dealing: An Empirical Example," *Journal of Marketing Research*, 8 (February), 118–20.

Montgomery, Alan and Peter Rossi (1993), "Bayesian Hierarchical Approaches to Estimating Price Elasticities," technical report, University of Chicago.

Narasimhan, Chakravarthi (1984), "A Price Discrimination Theory of Coupons," *Marketing Science*, 3 (Spring), 128–47.

Rossi, Peter and Greg Allenby (1993), "A Bayesian Method of Estimating Household Parameters," *Journal of Marketing Research*, 30 (May), 171–82.

Walters, Rockney (1991), "Assessing the Impact of Retail Price Promotions on Product Substitution, Complementary Purchase, and Interstore Sales Displacement," *Journal of Marketing*, 55 (April), 17–28.

Webster, Frederick (1965), "The 'Deal-Prone' Consumer," *Journal of Marketing Research*, 2 (May), 186–9.

Weisberg, Sanford (1985), *Applied Linear Regression*. New York: John Wiley and Sons, Inc.

White, Hal (1980), "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticty," *Econometrica*, 50, 483–99.